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Research-in-Progress

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Introduction

Recent years have witnessed the rapid proliferation of a new class of information technologies, commonly known as social media. Unlike traditional offline social networks, online social networks supported by social media platforms offer advanced structural formalisms to represent relationships and allow unprecedented amount of content creation and flow with persistent capture of such information at the finest level of granularity desired (Kane et al. 2014). Because of these novel capabilities, users can interact with each other in ways that were impossible in offline settings. For example, Facebook "friends" and Twitter "followers" offer a conduit for communication that differs in nature, frequency, reach, propagation speed and so forth, by many orders of magnitude. Similarly, online consumer reviews allow articulation and dissemination of user sentiment that can influence a customer's decision and also guide a manufacturer in planning and innovation. As a result, business researchers, particularly in the areas of Information Systems (IS) and marketing, are attempting to understand how the novel IT capabilities of social media platforms impact the flow of information about consumer sentiments, ultimately leading to purchase decisions.

In this paper, we define a new construct called *brand momentum* in the context of online platforms. We conceptualize brand momentum as aggregation of consumers' engagements with the brand measured in terms of temporal changes in their sentiments' frequency and intensity. Our research questions revolve around detecting brand momentum in social media settings as well through online e-commerce platforms, and the consequences of brand momentum on product sales. We hypothesize that brand momentum is a leading indicator of sales. The direct benefits of detecting brand momentum is that it would allow more accurate sales forecasting in the short term which has implications for inventory management, pricing, and upstream supply-chain decisions.

Literature Review

Researchers have used the unique characteristics of online social networks to define new constructs such as e-Word of mouth (Dellarocas 2003; Yu et al. 2013), social influence (Salganik 2006), bandwagon effect (Fu and Sim 2011), and so forth, and have attempted to measure their impact on various sales related metrics.

E-word of mouth (eWOM) is a key factor in influencing purchasing decisions of consumers online; for example, customers are paying more attention to online reviews when deciding what movies to watch (Rui et al. 2013) or in which stock to invest in (Wysocki 2000). Previous studies have found factors such as the number of online reviews (Duan et al. 2008; Hu and Liu 2004) and valence of online reviews as measured by the average star ratings (Chevalier and Mayzlin 2006; Dellarocas et al. 2007; Segal et al. 2012; Ye et al. 2011; Zhu and Zhang 2010) have an impact on product sales. Moreover, customer online reviews capture personal emotions, such as happiness, anger, sadness, love, and dislike, which potential customers read to make purchase decisions. Researchers have used such sentiments in online reviews, measured via sentiment analysis (Pang and Lee 2005), to forecast many economic phenomena such as box office attendance (Yu et al. 2012), political elections (Lee 2009), or product market share (Vinodhini and Chandrasekaran 2017).

Fu and Sim (2011) investigated a related concept of *bandwagon effect* in a longitudinal study and found that consumers leverage information on popular choices made by earlier consumers, i.e. decision-makers, and ultimately gravitate toward popular choices when faced with uncertain product consumption choices. The idea of bandwagon effect is related to social conformity phenomenon studied in psychology, where products that are popular early draw more attention and exposure than others, resulting in a snowball effect. Salganik (2006) study the notion of *social influence* on online marketplaces and the impact it has on sales. In the context of an online market, Salganik's experiment shows that hit products like songs, books, and movies are several folds more successful than other average products not because they are necessarily much better, but because consumers are influenced by the number of prior times each the product had been downloaded by previous participants..

These studies have implications for how social influence from consumer sentiments expressed through social media, product reviews and the like impact brand perception and hence performance. In the context of our study, we draw on the ideas of e-Word of mouth, social influence, and bandwagon effect to frame the idea of brand momentum exhibited on social platforms.

The notion of momentum in relation to brands has received little attention from researchers. In the context of pharmaceutical markets, Tebbey et al. (2009) define *"brand momentum as a quantitative, objective and comparative measure, derived from the temporal performance of the brand revenues."* In quantifying brand momentum, Tebbey et al. (2009) rely on concepts of size (measured by sales of product in the first year), speed (measured by annual growth rate for the first four years of a product), and sustainability (measured by number of consecutive years with 20% year over year growth), which are combined mathematically as:

$$\text{Brand Momentum} = [\text{size x speed}] + \text{sustainability}$$

While this framing of brand momentum is useful, it is based on the sales performance of brands and not on the engagement of consumers with the brand itself. Although increased engagement of consumers with a brand may lead to higher sales, the two are separate concepts. In our research, we are interested in measuring brand momentum from indicators of sentiment about the brand available through consumer-generated content such as social media postings and product reviews.

As noted from the extant literature, while constructs such as e-word of mouth, bandwagon effect, and social influence, play a role in understanding how brands might be perceived by consumers, the dynamic nature of a brand's perception in terms of the frequency and intensity of consumer sentiments expressed on online platforms has not been studied. We focus on this aspect, calling it brand momentum, and further aim to study it in relation to objective metrics such as product sales.

Proposed Research

Within the business research community, there is no general agreement regarding the meaning of the term brand momentum in the context of online platforms. We define brand momentum in terms of consumers' engagements with the brand measured in terms of temporal changes in their sentiments expressed through online consumer-generated content and feedback. The theoretical basis for brand momentum is in Consumer Brand Engagement (CBE) (Hollebeek et al. 2014). CBE measures a consumer's relationship with a brand in terms of three dimensions: *cognitive* (thinking about the brand), *emotional* (feeling about the brand), and *behavioral* (using the brand). In the offline context, these perceptive measures are directly obtained from the subject via a survey. In contrast, we plan to measure the indicators of brand momentum by extracting them from consumer-generated online content via text mining and sentiment analysis (as explained below). Also, CBE is a static concept, in the sense that it measures the state of a consumer's relationship with a brand at a point in time. On the other hand, momentum is a dynamic concept; brand momentum is an aggregation of temporal changes in consumers' engagements with the brand on various online platforms. We conceptualize brand momentum as a function of the rate of change in the frequency, polarity, and intensity of sentiments expressed on different types of consumer-generated content along the three CBE dimensions.

A number of studies have investigated the relationship between online reviews and sales; however the results are mixed. This lack of consistency has been attributed to multiple reasons (Duan et al, 2008). These include differences in reviewer influences - reviewer identity disclosure (Forman et al. 2008), reviewer trust (Banerjee et al. 2017); treating e-Word of mouth as an exogenous variable when, in reality, it may itself be influenced by sales; and not considering the heterogeneity in products about whom the reviews are written. Also, many of the studies have considered only easily quantifiable variables such as volume and valance of reviews. Few studies have attempted to mine the rich information contained in the textual part of the reviews and analyze the sentiments behind it. Those that have attempted to analyze the review text have not used a multidimensional, theoretically based concept such as CBE to measure the review characteristics that may impact the reader's decision to purchase a product.

We attempt to extract sentiments underlying an eWOM communication (online review or any type of social media post) along the three dimensions of CBE. Each dimension - cognitive, emotional, and behavioral - is theoretically grounded. A sentiment along the cognitive dimension is characterized by a review that shows knowledge and understanding of the product (e.g., "I normally wear a XL… but they run small - fit me like it was M", or "Nice bright color, just like it looked online… "). According to the source credibility theory, a communication's persuasiveness is affected by the perceived credibility of the source (Hovland and Weiss 1951). In the context of online platforms, we can expect that an eWOM from a "cognitively engaged" reviewer to be persuasive and thus affect the product purchase decision.

The emotional dimension is characterized by a sentiment of judgment (e.g., "Loved the look of it instantly" or "I splurged on this and, boy, did I make a blunder!"). It is closely related to the concept of arousal which is defined as the level of emotionality expressed in a communication. The "emotional engagement" of the source, when communicated via an eWOM, describes a psychological state that is likely to trigger a similar emotion in the receiver, leading to a reactive decision regarding a product purchase (Heilman 1997; Smith and Ellsworth 1985).

Finally, the behavioral dimension is described by terms that indicate usage of the product (e.g., "I practically live in these shorts all summer" or "I have several pairs in different colors"). The sentiments expressed in the behavioral dimension relate the fact that the reviewer has actually used and interacted with the product. If the reviewer is an extensive user of the product, then his/her experience with the product is deemed important. If there are a large numbers of positive behavioral sentiments expressed via eWOMS, the aggregate effect can give rise to the bandwagon effect and social influence phenomena mentioned earlier, where consumers leverage information on popular choices made by earlier consumers.

We hypothesize that brand momentum of a product is a leading indicator of changes in product sales; in particular, higher brand momentum leads to an increase in sales and lower brand momentum leads to a decrease in sales. We expect the brand momentum of a product to have a causal relationship with the changes in sales and that the changes in sales of a product will lag the brand momentum by a certain amount of time. Moreover, the extent of influence of brand momentum on the change in sales will depend on the nature of the product and also on the nature of the social media where sentiments are expressed.

For example, certain characteristics of product, such as niche products with narrow appeal (e.g., specialty products, fashion apparel), hedonic products (e.g., movies, songs) may have larger variations in brand momentum leading to larger impacts on sales. Tucker and Zhang (2011) found that popularity information benefits niche products with narrow appeal disproportionately more than broad appeal products.

Similarly, certain characteristics of consumer-generated content in the form of social media postings and online reviews may have a different effect on sales. These characteristics may vary in length, detail, and persistence of posts (e.g., on online product reviews). For example, tweets and Instagram posts provide only brief and transient information, while product reviews contain richer, more persistent information on aspects that the consumer experienced while engaging with the product.

Our research is aimed at estimating the strength of the relationship between brand momentum and changes in sales. We shall also test hypotheses regarding the moderating effect of product characteristics and online platform characteristics on the relationship between brand momentum and changes in sales. Finally, we plan to explore the amount of the time lag between brand momentum and its influence on sales. In our analysis, we will be analyzing data at the brand level rather than product level. As such, SKU-level information will not be used in the analysis.

Analytical Approach

Data Source

We are collaborating on this research project with a large manufacturer and retailer of everyday and specialty consumer products. The company owns a number of leading brands, which generate enormous amounts of user sentiment data on social media platforms like Facebook, Twitter, and Instagram. In addition, the company's products sold via its own website and also through large online retailers regularly generate customer reviews. In total, we have access to over 100,000 product reviews for over 40 product styles, over 10 million sales records at the SKU level, and over 100,000 online social media posts from Facebook, Instagram, and Twitter over the recent three-year period.

Analysis

The unstructured nature of the data to be analyzed in this project will require extensive pre-processing text analytics steps prior to analyzing brand engagement indicators such as sentiment and behavioral intentions. This will involve tokenization at the sentence level, and then applying a lemmatization or stemming to reduce inflectional forms of the words appearing in the text. This later step will depend on the approach planned ahead. We plan to experiment with a couple of key alternatives for text analytics. First, we will use a 'bag of words' or 'bag of n-grams' approach. In this approach, common stopwords will be removed and the ordering of words will be ignored. In another approach, we plan to use word embedding approaches including word2vec, fasttext, and glove. With this approach, co-occurrences of words can be taken into account. In both approaches, using sparse storage representations available in computational libraries such as scipy (in Python), effective computations on large text data can be handled. Following these steps, we plan to use lexicon-based feature engineering to analyze text 'documents' (reviews, tweets, etc.) along multiple dimensions. Toward this end, we will leverage existing lexicons for generic sentiments, while also developing new lexicons for capturing new constructs that are novel to this study and specific to the retail domain. Additionally, we will bring to bear, text analysis techniques that will help us analyze aspects such as double negation, uncertainty, and intentions. We recognize the challenge in dealing with unstructured data where nuances such as sarcasm may not be captured in a perfect manner, though the advantage of large volume of data will help mitigate the concern of excessively biased results due to such influences. The numeric features generated will then be analyzed using machine learning algorithms.

Sentiment analysis has received tremendous attention and interest from scholars over the past decade (Mostafa 2013; Pang and Lee 2008; Zhou et al. 2015). Its recent popularity is mostly due to advances of machine learning methods in language processing and information retrieval, availability of larger datasets, and the advances of commercial intelligence applications (Yu et al. 2013). Sentiment analysis is a combined application of computational linguistics, natural language processing, and text mining to detect opinions, sentiments, emotions, and subjectivity in text (Li and Wu 2010; Liu 2010). It involves two tasks: detecting which text segments (e.g., sentences) contain sentiment signals, and determining the polarity and strength of the sentiment (Escudero et al. 2000). In our research, we plan to use supervised machine learning algorithms to classify a sentiment's intensity and polarity in online reviews and social media comments by first assigning known class labels to objects in a training data set. These algorithms include k-Nearest Neighbors, Naïve Bayes, and Support Vector Machines (Khan et al. 2017). We also plan to leverage recent advances in machine learning, applying deep learning techniques (e.g., convolutional neural networks) and ensemble modeling to find the models that perform the best and are generalizable. Volume will be measured as the total number of reviews and number of online conversations by product over many specific time-windows. Brand momentum will be computed as a function of change over time in frequency, intensity, and polarity of sentiments expressed about a product.

In order to test our hypothesis, we will take a time-window based analysis of sentiments to reflect change in brand momentum. Once we quantify brand momentum, we plan to investigate if user-sentiment perspective in online reviews is correlated with product sales. We will also test the moderating effects of product and online platform characteristics on the relationship between brand momentum and product sales.

Conclusion

Brand momentum, especially in the context of online social networks, is a new concept. A major contribution of this paper is in defining this concept, hypothesizing it as a leading indicator of product sales, and understanding that the characteristics of the focal products and the online platforms where they are discussed can alter the nature of this relationship. We plan to complete this research with the help of data obtained from a leading manufacturer of retail products and by pre-processing and analyzing the data using advanced sentiment analysis and machine learning techniques. This research, when completed, will have a direct benefit for businesses in similar industries. Early detection of brand momentum would allow them to more accurately forecast product sales in the short-run. For those businesses who have flexible manufacturing and sourcing capabilities, responsive supply-chain networks, and agile marketing capabilities detecting brand momentum can lead to major benefits, such as capturing additional sales from demand spikes or lowering lost sales, reducing distribution cost by streamlining upstream supply-chain decisions, and even increasing revenue by making more informed pricing decisions.

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